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Institutional trading, momentum and idiosyncratic volatility

Abstract

Based on the fact that different investor clienteles are attracted to different share price levels and they have distinct trading behavior. This paper examines the relation between idiosyncratic volatility and future stock returns by focusing on different share price portfolios. The author shows that the future stock return is positively related to idiosyncratic volatility for high-priced stocks and negatively related for the low-priced stocks by showing that investors may react differently to idiosyncratic volatility depending on its source. Idiosyncratic volatility may be associated with momentum and skewness of stock returns for institutionally owned high-priced stocks and retail owned low-priced stocks, respectively.

Keywords: share price, skewness preference, momentum, investor clientele, idiosyncratic volatility.
JEL Classification: G11, G17, G12.

Introduction

I study the relationship between idiosyncratic volatility and future stock returns by focusing on different share price portfolios. Such a separation has important implications for two reasons: first, different investor clienteles are attracted to different share price levels; second, investor reaction to different levels of idiosyncratic volatility may differ depending on its source.

In terms of investor clienteles Fernando, Krishnamurthy and Spindt (1999), and Schultz (2000) both provide empirical evidence that stocks with lower share prices are more attractive to individual investors. Kumar (2009) also shows that it is retail or individual investors who prefer stocks with lottery like characteristics. In contrast, Falkenstein (1996) and Gompers and Metrick (2001) both show that institutions avoid investing in low-priced stocks. Hence, there are distinct investor clienteles based on the share price level, which may have implications for stock returns since these clienteles may have different preferences towards the higher moments of the return distribution.

For example, Barberis and Huang (2008) show by using cumulative prospect theory that some investors will take large undiversified positions in lottery-like stocks that are small and positively skewed. In this framework skewness preference dominates the retail investors' trading behavior. However it has less relevance for institutional investors, which hold more diversified portfolios. An implication of this type of investor behavior is that there is a negative relation between the level of retail ownership and future stock returns.

In contrast, Gompers and Metrick (2001) document a positive relation between institutional ownership and future stock returns. This is due to short-term momentum trading behavior for this type of investor. For example, Grinblatt et al. (1995), Chan et al. (1996) and Sias and Starks (1997) all show that institutional investors are more likely to engage in short-term momentum trading. As Vayanos and Woolley (2013) explain this institutional preference is based on trading forced on fund managers by fund inflows and outflows.

Several studies associate idiosyncratic volatility with either skewness or momentum. It is because in terms of its source, high idiosyncratic volatility may be caused by different patterns of share price behavior which may be important for different types of investors. For example, apart from simply exhibiting high random stock price behavior, high idiosyncratic volatility may result from extreme outliers associated with high skewness. On the other hand, continuous upward or downward price movements caused by momentum trading can also result in high estimated idiosyncratic volatility. Consequently higher idiosyncratic volatility may be associated with higher skewness for some stocks, whereas for others it may be associated with momentum trading. Given the different preferences of retail and institutional investors this differing source of estimated idiosyncratic volatility may explain the anomalous relationship between idiosyncratic volatility and future stock returns. For example, Mitton and Vorkink (2007) and Boyer, Mitton and Vorkink (2009) predict lower expected returns for stocks with high idiosyncratic volatility due to skewness preference as in Prospect Theory. On the other hand, Vayanos and Woolley (2013) show that momentum stocks are also high idiosyncratic volatility stocks.

My basic hypothesis is, therefore, that different investor clienteles, based on the level of the share price, react differently to estimated idiosyncratic volatility. For low-priced stocks, I hypothesize that retail investors treat higher idiosyncratic volatility as a proxy for a more right skewed return distribution. Consequently, retail investors are willing to pay a premium for higher estimated idiosyncratic volatility, resulting in lower and even negative future returns. In contrast, for high-priced stocks higher idiosyncratic volatility is associated with momentum due to institutional investors' short-term trading which then generates positive future returns. I call this differential impact of idiosyncratic volatility on future stock returns a clientele based explanation.

In contrast to my hypothesis the existing empirical literature has largely focused either on different methodologies for estimating idiosyncratic volatility, such as equal versus value weighted estimates, using industry residuals rather than those from the Fama-French (1992) three factor (Fama-French model, hereafter) or estimating the relation over different time periods. For example, the negative relation between lagged idiosyncratic volatility and future stock returns was originally estimated by Ang et al. (2006; 2009). However, Lehmann (1990), Goyal and Santa-Clara (2003), and Fu (2009) all present evidence of a positive relation using different methodologies, while Bali et al. (2005) and Bali and Cakici (2008) find there is no significant relation at all. A recent paper by Bali et al. (2011) examines the impact of maximum return on the future stock returns and shows that after controlling for it negative relation between lagged idiosyncratic volatility and future stock returns disappears.

The contribution of this paper is that by using the share price as a proxy for the ownership clientele[1] I show that for different share price portfolios the relation between idiosyncratic volatility and future stock returns differs: it is negative for low and mid-priced stocks but positive for high-priced stocks. This result is strong for excess returns estimated using the Fama-French model but also is robust with respect to using the Carhart model that includes a momentum factor, except for the high-priced stocks where momentum is important. After controlling for momentum the positive relation between idiosyncratic volatility and future stock returns largely disappears for high-priced stocks. In other words, for stocks predominantly held by retail investors there is a negative relation between lagged idiosyncratic volatility and future stock returns regardless of momentum. However, for the high-priced stocks favoured by institutional investors idiosyncratic volatility is closely associated with momentum through the Carhart model.

This paper is the first that establishes a link between idiosyncratic volatility and the share price differentiated effects of skewness and momentum. In particular it documents that the skewness effect also noted by Boyer et al. (2009) is incomplete explanations for the impact of idiosyncratic volatility. Skewness preference cannot be a general explanation given that the equity market is dominated by institutions holding well diversified portfolios[2]. In this sense the results in this paper follow from a deeper understanding of the interaction between ownership structure and security returns.

The rest of the paper is organized as follows. In Section 1, I introduce the data, methodology and summary statistics. In Section 2, I examine the impact of idiosyncratic volatility on future returns for different share price portfolios using both a portfolio approach and cross-sectional regression analysis. The last section concludes the paper.

1. Data, methodology and summary statistics

All stock related data are derived from the Center for Research in Security Prices (CRSP) database for U.S. listed stocks from 1963-2008. The Fama-French three factor time series data as well as the momentum and short-term reversal factors are downloaded from Kenneth French's web page. Institutional ownership data is gathered from the Thomson Reuters, 13F Institutional Holding (CDA/Spectrum s34) database. It is quarterly data and only available for the period 1980-2008. As a proxy for institutional ownership I use the fraction of shares held by institutions for the preceding quarter out of the total shares outstanding. Institutional holding for each stock is then calculated each quarter.

For each stock, idiosyncratic volatility is estimated as the standard deviation of the residuals, $\sqrt{(\mathrm{var}(\varepsilon_t^i)}$ from a three-factor model of daily returns in excess of the risk-free rate[3].

Every month, t, stocks are sorted into three portfolios based on their closing stock price in month t–1. Stocks that are above \$2 and less than \$10 are called low-priced, and stocks that are above \$100 are called high-priced stocks[4]. Stocks that are in between \$10 and \$100 are considered to be mid-priced stocks.

1.1. Summary statistics. Table 1 shows key characteristics for the share price sorted portfolios such as average size, skewness, idiosyncratic volatility and turnover. Low-priced stocks have an equally weighted average price of \$5.91 and the smallest size based on

[1] Estimating retail holdings of a stock is not easy. Studies in the literature use the Study of Security Markets (ISSM) and Trade and Quote (TAQ) data sets. Small size trades are often used for indicating retail holdings, this has been questioned in a recent study by Campbell et al. (2009) which provides evidence that extremely small buys below \$2,000 also predict increasing institutional ownership. Han et al. (2013) also estimate the impact of retail investor holdings by using data from 1983-2000.

[2] Simkowitz and Beedles (1978) show that skewness disappears in large diversified portfolios.

[3] This study only uses idiosyncratic volatility estimated from stocks that have more than 17 daily observations due to possible biases due to infrequent trading.

[4] I exclude penny stocks with very low share prices under \$2. These stocks have very little commonality with other low-priced stocks.

market capitalization, that is, the number of shares outstanding multiplied by the previous end of month share price. As might be expected firm size increases monotonically with share price; the same relation is seen for idiosyncratic volatility. Low-priced stocks have higher idiosyncratic volatility, whereas high-priced stocks have relatively low idiosyncratic volatility. As a result, idiosyncratic volatility declines monotonically as the share price increases. Moreover, there is a negative relation between individual stock return skewness and the share price: the lower the share price the higher the skewness. Finally, turnover increases as the share price increases. If I use turnover as a proxy for liquidity, then low-priced stocks are relatively illiquid compared to mid and high-priced stocks.

Table 1. The stock characteristics of different share price portfolios

		Size	*Skew*	*Ivol* %	*Turnover**100
Low-priced	Mean	3.11	0.31	3.27	0.65
	Std. dev.	0.87	0.22	0.67	0.43
Mid-priced	Mean	4.69	0.23	2.49	0.80
	Std. dev.	0.73	0.18	0.76	0.69
High-priced	Mean	7.22	0.17	1.32	1.79
	Std. dev.	0.60	0.31	0.53	2.96
High-low		4.11	-0.15	-1.95	1.14
Difference		(90.68)	(-9.26)	(-53.32)	(7.78)

Notes: *Size* is the natural logarithm of market capitalization; *Ivol* is the idiosyncratic volatility, *Skew* is the skewness of the simple unadjusted daily stock returns and *Turnover* is the trading volume divided by the number of shares outstanding. All values show the monthly averages. High-low indicates high-priced minus low-priced portfolio characteristics. *t*-values in parentheses show statistical significance.

Probably for the above reasons previous research has shown that low-priced stocks are not attractive to institutional investors and are, therefore, mainly held by retail investors. By construction this means that high-priced stocks are the opposite, that is, they are mainly held by institutional investors. Table 2 summarizes key information about the ownership structure of the price sorted portfolios. Consistent with earlier studies low-priced stocks are more likely to be held by retail investors. Over the period 1980-2008 the "depth" or percentage institutional ownership of low-priced stocks was below 20% per quarter, whereas for high-priced stocks it was well over double that. Further there is a monotonic increase in institutional ownership as the share price increases where, for example, mid-priced stocks have an average 32% institutional ownership. In panel B the same data is parsed for low and high idiosyncratic volatility stocks respectively, which tends to indicate an institutional investor preference for low idiosyncratic volatility stocks, except for the lowest priced stocks.

Table 2. The share price and institutional holdings

Panel A. Institutional ownership and price sorted portfolios

	Frac. of shares	Diversity of inst owners
Low-priced	18.31	1.20
Mid-priced	32.17	5.01
High-priced	41.31	14.00
High-low	22.99 (20.03)	12.80 (19.34)
High-mid	9.14 (6.25)	9.00 (13.56)

Panel B. Institutional ownership and Ivol-price sorted portfolios

	Low Ivol		High Ivol		High-low Ivol	
	Frac. of shares	Diversity of inst. owners	Frac. of shares	Diversity of inst. owners	Frac. of shares	Diversity of inst. owners
Low-priced	11.67	0.92	16.06	0.97	4.39 (15.33)	0.05 (0.02)
Mid-priced	30.75	6.60	16.52	1.36	-14.23 (-10.46)	-5.24 (-3.55)
High-priced	45.78	16.98	35.6	7.2	-10.20	-9.75
High-low	34.11 (60.13)	16.06 (25.28)	19.52 (14.17)	6.26 (13.07)	(-18.25)	(-8.36)

Notes: The fraction of shares that is held by institutions for the preceding quarter is computed as the total number of shares that managers hold in a quarter divided by the total numbers of shares. Diversity of institutional owners is computed as the total number of institutions that hold the stock divided by the total number of institutions. Ivol is idiosyncratic volatility. The sample includes quarterly data from 1980-2008. Panel A shows institutional ownership for price sorted portfolios and Panel B shows institutional ownership for idiosyncratic volatility and price sorted portfolios. *t*-values in parentheses show statistical significance of mean differences.

Table 2 also shows that high-priced stocks are held by many different institutions, for example, whereas a high-priced stock on average has 41.3% institutional ownership it is also held by 14% of all managers. In contrast, low-priced stocks have only 18.3% institutional ownership and are only held by 1.2% of all managers. Interestingly although significant fractions of mid-priced stocks are held by institutions, they are held by relatively few managers compared to high-priced stocks. This difference in the number of institutions owning the stock as well as the amount they own may explain why I see differences in future stock returns for mid and high-priced stocks.

2. Idiosyncratic volatility and stock returns: impact of share price

2.1. Time-series results. In this section I examine the relationship between lagged idiosyncratic volatility and future stock returns for different share price portfolios by sorting stocks into five quintiles by their previous month's idiosyncratic volatility and three groups by their previous month's share price. Abnormal returns are initially estimated with respect to the Fama-French three factor model. This sorting procedure controls for the level of the share price to analyze the conditional relation between idiosyncratic volatility and future stock returns. Similarly, it controls for idiosyncratic volatility to analyze the conditional relation between the share price and future stock returns.

Panel A of Table 3 shows the Fama-French alphas for each idiosyncratic volatility and share price sorted portfolio. For low and mid-priced stocks there is a clear negative relation between idiosyncratic volatility and future stock returns. In contrast, for high-priced stocks, although the relation is less significant it is positive. This means that a trading strategy of high minus low idiosyncratic volatility stocks earns an average -1.64% per month for low-priced stocks, -0.99% for mid-priced stocks, but +1.33% per month for high-priced stocks. These alphas translate into very significant annual risk adjusted portfolio rates of return. However, these alphas are conditional on the level of the share price. In fact, the literature on idiosyncratic volatility shows that negative future alphas on high minus low idiosyncratic volatility ignores the share price impact.

Panel A of Table 3 also helps reconcile some of the previous results in the literature, since high idiosyncratic volatility stocks as Table 1 indicated are mainly low-priced stocks with low market capitalizations. However, the negative relation between idiosyncratic volatility and future stock returns is less pronounced in equally weighted portfolios where low priced stocks are more numerous than it is in value weighted portfolios, where the high price-high market capitalization stocks have more weight. It also shows the results of a trading strategy based on the share price, that is, a trading strategy of high minus low-priced stocks. This strategy earns positive alphas which increase with the level of idiosyncratic volatility. For example, there are very high positive abnormal returns for the strategy using high idiosyncratic volatility stocks, whereas for low idiosyncratic volatility stocks the alphas are negligible and insignificant. It appears that a high minus low price trading strategy works better as idiosyncratic volatility increases and at 2.98% per month for the highest idiosyncratic volatility group it dominates the results of a high minus low idiosyncratic volatility strategy. However, the similarity in results indicates the close relationship between idiosyncratic volatility and the level of the share price.

In Panel B of Table 3 are the same tests using the four factor Carhart model to estimate abnormal returns. Of interest is that both the results noted above for the Fama-French alphas continue. However, they are obviously weaker, since I am adding another risk factor, which reduces the excess returns. For example, there is still a clear negative relation between idiosyncratic volatility and future stock returns for low and mid-priced stocks and the alphas continue to decrease as the share price increases. Further a high minus low idiosyncratic volatility strategy continues to earn similar abnormal returns to those based on the Fama-French model.

However, this is not the case for high-priced stocks, where the positive alphas are all much reduced, are usually insignificant and even turn negative for the highest idiosyncratic volatility portfolio that previously generated very high alphas. This indicates that the previous positive Fama-French alphas are largely driven by short-term momentum. Instead there is now a universally negative relation between idiosyncratic volatility and future stock returns regardless of the share price.

Panel B of Table 3 indicates that the high positive loadings of high-priced stocks on momentum reduce their alphas with the most pronounced effect coming in the highest idiosyncratic volatility group. This also affects the returns from the high minus low-priced trading strategy. Note that as the idiosyncratic volatility increases the Carhart alphas also increase as before, but as I move into the highest idiosyncratic volatility quintiles the Carhart alphas fall and even turn negative for the highest group. Clearly the effect of momentum in the Carhart model is closely associated both with the level of the share price and idiosyncratic volatility and affects the high idiosyncratic volatility-high share price portfolio the most. As a result, the high minus low share price trading strategy is not as effective when judged by the Carhart alphas: although the strategy still generates higher alphas as idiosyncratic volatility increases they are not as significant.

Table 3. The share price and idiosyncratic volatility effect on stock returns

Panel A. Fama-French alphas						
Ivol rank						
	Low	2	3	4	High	High-low
Low-priced	0.13 (0.88)	0.07 (0.46)	0.02 (0.11)	-0.45 (-3.03)	-1.51 (-8.50)	-1.64 (-5.59)
Mid-priced	0.07 (1.47)	0.05 (1.00)	0.02 (0.27)	-0.32 (-3.19)	-0.92 (-5.36)	-0.99 (-2.51)
High-priced	0.13 (0.95)	0.23 (1.12)	1.41 (4.16)	1.16 (1.95)	1.47 (1.78)	1.33 (1.57)
High-low	0.00 (0.20)	0.16 (0.41)	1.40 (3.08)	1.61 (2.18)	2.98 (2.80)	
Panel B. Carhart model alphas						
	Low	2	3	4	High	high-low
Low-priced	0.11 (0.66)	0.24 (1.57)	0.30 (1.99)	-0.20 (-1.17)	-1.37 (-6.13)	-1.48 (-4.54)
Mid-priced	0.12 (2.09)	0.11 (1.67)	0.07 (1.00)	-0.27 (-2.23)	-0.94 (-4.52)	-1.06 (-2.23)
High-priced	-0.07 (-0.44)	0.08 (0.36)	0.85 (2.35)	0.54 (0.80)	-0.28 (-0.32)	-0.21 (-0.30)
High-low	-0.18 (-0.47)	-0.16 (-0.18)	0.54 (1.41)	0.74 (0.90)	1.09 (1.52)	

Notes: Sample period is July 1963 to December 2008. Panel A shows the Fama-French 3 factor alpha estimates. Panel B shows Carhart 4 factor alpha estimates. High-low indicates high-priced minus low-priced portfolio Fama-French and Carhart alpha. High-low Ivol indicates high-Ivol minus low-Ivol portfolio Fama-French and Carhart alpha. Robust Newey-West (1987) *t*-values are in parentheses.

In summary, I show that there is a positive relation between idiosyncratic volatility and future stock returns when I focus on high-priced stocks and a negative relation when I focus on low and mid-priced stocks. However, the strength of this relationship depends on whether I use Fama-French or Carhart alphas. In understanding why this is the case I show the momentum coefficients. These coefficients show a very interesting pattern.

For example, for high-priced stocks note that the coefficients on momentum consistently increase with the level of idiosyncratic volatility and are universally positive. In contrast, for low-priced stocks the momentum coefficients are all negative and tend to decrease with idiosyncratic volatility whereas for mid-priced stocks they are all negative with no pattern at all. The negative signs for mid and low priced stocks would indicate return reversal, whereas the opposite is indicated by high priced stocks. However, clearly the Carhart momentum coefficients are strongly affected by both the share price and idiosyncratic volatility.

The major insight from Table 3 and Table 4 is that how the excess returns are estimated has a huge influence on whether there are abnormal returns to both a share price or idiosyncratic volatility based trading strategy. In particular the very high momentum coefficient of 1.07 on high-priced high idiosyncratic volatility stocks explains how the very high Fama-French alphas of 1.47% become negative Carhart alphas of -0.28%. Further since these are high priced (market capitalization) stocks they have an impact on whether portfolio returns are calculated as equally or value weighted returns unless I control the share price[1].

Table 4. Momentum coefficient estimates from Carhart model

	Ivol rank				
	Low	2	3	4	High
Low-priced	-0.06 (-1.62)	-0.22 (-4.77)	-0.31 (-5.11)	-0.31 (-3.58)	-0.24 (-1.84)
Mid-priced	-0.01 (-0.41)	-0.05 (-1.57)	-0.06 (-1.86)	-0.07 (-1.01)	-0.08 (-0.80)
High-priced	0.09 (2.08)	0.26 (5.18)	0.46 (5.33)	0.69 (3.34)	1.07 (3.33)

Note: Table shows the momentum coefficient estimates from Carhart model. Robust Newey-West (1987) *t*-statistics are in parentheses.

2.2. Fama-MacBeth cross-sectional regression estimates. In this section, I run Fama-MacBeth cross-sectional regressions in order to check the results from the portfolio approach. The dependent and independent variables are standardized such that each variable has a mean of zero and a standard deviation of one. I follow the Pontiff (1996) methodology to correct the Fama-MacBeth standard errors for potential serial correlation[2]. To ensure that extreme values do not affect the results, I winsorize all variables at their 0.5 and 99.5 percentile levels.

Table 5 reports estimates from the monthly Fama-MacBeth cross-sectional regressions in which the monthly stock return is the dependent variable. In column (1), I use the same exact specification and time period (1980-2003) used in Ang, Hodrick, Xing and Zhang (2009). As seen from the table, the results in column (2) for the period of 1963-2008 are in line with theirs; lagged idiosyncratic volatility has a strong negative coefficient -0.038 (*t*-statistic = -6.41). Because momentum is a key variable, *the base model* in column (3) shows the same specification as in column (1) without the momentum variable (past six-month return), and now the

[1] In my case, I have similar results when portfolio returns are calculated using equal weights due to the similar size of stocks in each price portfolio.

[2] Standard errors that are robust are constructed by regressing the time-series of the parameter estimates on an intercept term and modeling the residuals as an autoregressive process. The standard error of the intercept term is used as the correct standard errors.

coefficient on the lagged idiosyncratic volatility is slightly higher, -0.040 (t-statistic = -6.61). In column (2), I see that the momentum variable has a significantly positive coefficient +0.023 (t-statistic = +5.85) that takes away some of the negative impact of idiosyncratic volatility, but not all.

Column (4) shows the results when I add share price. It enters into the equation as positive with a coefficient of +0.068 (t-statistic = + 4.35). This coefficient means stocks with high share prices in a month earn higher returns in the following month. Although controlling for the share price reduces the negative impact of idiosyncratic volatility on future stock returns (coefficient = -0.038, t-statistic = -6.39), it still is significantly negative. This is because the low- and mid-priced stocks' idiosyncratic volatility dominates the negative relation, and they represent the majority of the data.

To see the interaction between idiosyncratic volatility and share price, I run the Fama-MacBeth cross-sectional regressions with *High Price* × *High Ivol* and *Low Price* × *High Ivol.* Column (5) shows the results for the base model, and column (6) adds the past six-month return and lagged return. The past six-month return controls for momentum, and the lagged return controls for return reversal. In column (5), I find that, all else being equal, stocks with high idiosyncratic volatility earn +0.070% higher monthly returns (t-statistic= +2.77) when those stocks also have a high share price. On the contrary, stocks with a low share price and high idiosyncratic volatility earn +0.010% higher monthly returns (t-statistic = +1.27). After adding momentum and short-term reversal variables, I find that high idiosyncratic volatility stocks earn +0.075% higher monthly returns (t-statistic = +2.61) when those stocks also have a high share price. Now, low-priced high idiosyncratic volatility stocks don't earn higher returns (+0.001% higher monthly returns, t-statistic = +0.09). This is because the short-term reversal variable takes away the volatility's power. These results are in line with my portfolio approach in which a high-priced portfolio with high idiosyncratic-volatility earns more than a high-priced portfolio with low-idiosyncratic volatility.

As a robustness check, I also estimate models in columns (7-8) and (9-10) for sub-samples with high-priced and low-priced stocks respectively. In line with the coefficient estimates of *High Price* × *High Ivol* and *Low Price* × *High Ivol*, I find that the relation between idiosyncratic volatility and future stock returns is significantly negative for low-priced stocks but has no relation for high-priced stocks when I use the base model in columns (7) and (9). However, momentum and short-term reversal variables enter with a different magnitude for each price subsample. The momentum has a higher positive impact on the next month's return for high-priced stocks (coefficient on momentum = +0.029, t-statistic = +5.47) than for low-priced stocks (coefficient on momentum = +0.012, t-statistic = +2.23). On the other hand, this month's return has a higher negative impact on the next month's return for low-priced stocks (coefficient on momentum = -0.08, t-statistic = -11.77) than for high-priced stocks (coefficient on momentum = -0.01, t-statistic = -2.12). This evidence highlights that high-priced (low-priced) stocks display less (more) short-term reversal and more (less) momentum.

Table 5. Idiosyncratic volatility, share price, and stock returns: Fama-MacBeth cross-sectional regression estimates

Variable							High-priced		Low-priced	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	0.002	0.001	0.001	0.002	0.000	0.002	0.014	0.005	-0.268	-0.177
	2.400	1.720	1.380	3.020	0.070	1.270	1.240	0.420	-3.690	-2.790
Lagged Ivol	-0.031	-0.038	-0.040	-0.038	-0.041	-0.025	0.003	-0.005	-0.046	-0.026
	-3.350	-6.410	-6.610	-6.390	-7.380	-4.330	0.300	-0.480	-10.370	-5.520
Beta	0.054	0.066	0.068	0.069	0.069	0.065	0.057	0.050	0.080	0.074
	4.940	8.070	8.290	8.410	8.420	7.600	2.700	3.620	11.400	10.670
SMB beta	0.006	0.016	0.016	0.016	0.016	0.015	-0.006	-0.008	0.028	0.027
	0.830	2.590	2.510	2.520	2.490	2.490	-0.590	-0.840	4.070	4.050
HML beta	-0.021	-0.017	-0.016	-0.017	-0.017	-0.017	0.005	0.007	-0.027	-0.026
	-2.230	-2.510	-2.420	-2.490	-2.540	-2.490	0.430	0.600	-3.890	-3.920
Size	-0.026	-0.032	-0.030	-0.039	-0.039	-0.035	-0.017	-0.015	-0.105	-0.099
	-5.530	-6.530	-6.000	-8.060	-8.080	-7.090	-3.720	-3.270	-14.280	-13.410
B-to-M	0.012	-0.005	-0.005	-0.005	-0.005	-0.004	-0.056	-0.051	0.006	0.008
	0.990	-0.550	-0.590	-0.540	-0.580	-0.500	-1.660	-1.710	0.890	1.120
Past six-month return	0.019	0.023				0.020		0.029		0.012
	4.070	5.850				4.680		5.470		2.230

Table 5 (cont.). Idiosyncratic volatility, share price, and stock returns: Fama-MacBeth cross-sectional regression estimates

							High-priced		Low-priced	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lagged return						-0.058		-0.010		-0.080
						-12.210		-2.120		-11.770
Lagged price				0.068	0.067	0.069				
				4.35	4.280	4.220				
High price × High Ivol					0.070	0.075				
					2.770	2.610				
Low price × High Ivol					0.010	0.001				
					1.270	0.090				
Average number of stocks	6385	5229	5255	5255	5255	5229	359	358	1737	1724
Adjusted R^2	0.043	0.057	0.051	0.053	0.055	0.066	0.140	0.166	0.043	0.056

Note: Dependent variable is the return of stock *i* in month *t*. The lagged idiosyncratic volatility (*Lagged Ivol*); the *Ivol* in month *t* is defined as the standard deviation of the residual from the Fama and French three-factor model where daily returns from month *t* are used to estimate the model. Other independent variables are: market beta (*Beta*), small-minus-big beta (*SMB beta*), high-minus-low beta (*HML beta*), and they are all measured contemporaneously. Firm size (*Size*), book-to-market ratio (*B-to-M*), past six-month return (*Past Six-Month Return*), past month's return (*Lagged return*), past month's closing share price (*Price*), past month's idiosyncratic skewness (*Lagged Iskew*), and the past month's turnover (*Lagged turnover*). Firm size and six-month returns are measured in the previous month, and the book-to-market measure is from six months ago. Salient numbers are denoted in bold.

2.3. Determinants of idiosyncratic volatility. In this section, I discuss the determinants of idiosyncratic volatility. Idiosyncratic volatility can result from different price movements associated with momentum, skewness and volatility respectively that is continuous up or down price movements over the month; a large one time price increase or decrease during the month, or simply high volatility that is lots of random price movement. To test whether it is skewness or momentum that drives idiosyncratic volatility I run a Fama-MacBeth (1973) style regression of the natural logarithm of idiosyncratic volatility on the natural logarithm of the individual stock return skewness and the past six month's cumulative return with other control variables, such as size, turnover, past price, and past idiosyncratic volatility. The six month cumulative return is commonly used as a momentum factor since it differentiates between winners and losers. The results are reported in Table 6 for different models including various combinations of explanatory variables.

In each cross-sectional regression, I use standardized variables. Note first that across all model specifications idiosyncratic volatility increases with systematic risk (beta), size and turnover and decreases with the level of the share price. In particular the share price effect is much stronger than the market capitalization effect and trading goes hand in hand with higher idiosyncratic volatility. In terms of the impact of skewness in Model 1 the coefficient on the individual stock return skewness is 0.101 which is significant at the 1% level confirming that idiosyncratic volatility is positively associated with right skewed distributions. Model 2 shows that this still holds even when past idiosyncratic volatility is also included in the model. However, in Model 3, I add skewness interacted with the share price and find that the interaction is statistically significant and negative, -0.098. Hence, I confirm that the effect of individual stock return skewness on idiosyncratic volatility decreases significantly with the share price. The implication is that as the share price increases the skewness associated with idiosyncratic volatility decreases so that skewness preference is less a factor for high-priced-high idiosyncratic volatility stocks. In contrast it is the low-priced-high idiosyncratic volatility stocks that do in fact have lottery like characteristics.

In Models 4 and 5, I add the momentum variable. In Model 4, I see that past winners have lower idiosyncratic volatility whereas Model 5 indicates that the momentum effect is almost entirely due to higher priced stocks, since the direct coefficient is insignificant whereas the interaction term is positive and highly significant at 0.071. This indicates that the higher the share price, the higher the impact of momentum on next period's idiosyncratic volatility.

Finally in Model 6, I include all variables and the results are very similar. The upshot is that the higher the share price the lower the impact of skewness on idiosyncratic volatility and the greater the impact of momentum. This analysis confirms the findings that momentum is a more significant determinant of idiosyncratic volatility than skewness for high-priced stocks.

Table 6. Fama-MacBeth regressions: idiosyncratic volatility, skewness and momentum

	(1)	(2)	(3)	(4)	(5)	(6)
Beta	0.042 (17.195)	0.031 (15.129)	0.030 (15.120)	0.028 (14.496)	0.028 (14.560)	0.028 (14.470)
Size	0.018 (4.934)	0.022 (8.529)	0.014 (5.800)	0.015 (5.549)	0.010 (3.660)	0.004 (1.554)
Price	-0.650 (-119.301)	-0.398 (-88.368)	-0.390 (-83.000)	-0.362 (-77.968)	-0.358 (-73.496)	-0.352 (-68.809)
Turnover	0.198 (46.507)	0.146 (40.358)	0.143 (40.521)	0.147 (39.139)	0.143 (37.952)	0.140 (37.659)
Skewness	0.101 (54.050)	0.099 (63.472)	0.110 (61.822)	0.097 (50.950)	0.097 (53.731)	0.108 (52.031)
Past Ivol		0.412 (85.583)	0.408 (85.978)	0.433 (84.998)	0.419 (82.964)	0.415 (81.821)
*Skewness*Price*			-0.098 (-53.782)			-0.090 (-36.893)
Momentum				-0.008 (-2.542)	-0.001 (-0.353)	-0.002 (-0.754)
*Momentum*Price*					0.071 (18.983)	0.066 (16.597)
N	4643	4615	4615	4483	4483	4483
R^2	0.49	0.59	0.60	0.60	0.61	0.62

Notes: Dependent variable is the natural logarithm of one plus idiosyncratic volatility over the current month. Independent variables: *Beta* is monthly stock beta estimated by the equation (1). *Size* is the natural logarithm of market capitalization over the current month. *Price* is the natural logarithm of one plus the previous period's stock price. *Turnover* is the natural logarithm of one plus turnover over the current period. *Skewness* is calculated by using daily data over a month *t*. *Past Ivol* is idiosyncratic volatility in month *t*-1. *Momentum* is the cumulative simple return over the past six months. Robust *t*-values are in parentheses.

Conclusion

In this paper, I show that there is a negative relation between idiosyncratic volatility and future returns for low and mid-priced stocks; high idiosyncratic volatility stocks earn negative abnormal returns. However, there is an opposite relation for high-priced stocks; high idiosyncratic volatility stocks earn higher future returns. However, I show that after momentum is considered, there is still a negative relation between idiosyncratic volatility and future returns for low and mid-priced stocks, but there is no relation for high-priced stocks, since momentum is a significant determinant of the high idiosyncratic volatility of high-priced stocks. I also show that high idiosyncratic volatility stocks have more skewness if the share price is lower and more momentum if the share price is higher. Finally, I conclude that the difference between the signs of the relation between idiosyncratic volatility and future returns for low and high-priced stocks may be due to this difference in what causes the higher idiosyncratic volatility and their investor clienteles. The results are consistent with the idea that idiosyncratic volatility is valued by retail investors since it is associated with higher skewness, whereas for high priced stocks it is associated with momentum trading by institutions.

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